

AI - Based Food Freshness Detection and Recipe Recommendation System

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Abstract

Food spoilage and wastage are major concerns in household and small-scale food management due to the absence of reliable freshness assessment methods. This paper proposes an AI-based food freshness detection and recipe recommendation system using computer vision techniques. A Convolutional Neural Network (CNN) is trained on labeled food images to classify items into fresh, medium, and spoiled categories. Image preprocessing through normalization is performed to enhance model performance. Based on the predicted freshness level, the system recommends suitable recipes to encourage timely food consumption. The solution is entirely software-based, making it cost-effective and easy to deploy. Experimental results demonstrate satisfactory classification accuracy, validating the effectiveness of the proposed approach.

Keywords: Food Freshness Detection, Convolutional Neural Network, Computer Vision, Image Classification, Food Waste Reduction.

1. Introduction

Food wastage has emerged as a major global concern, impacting food availability, household expenditure, and environmental sustainability. A large share of this waste occurs at the consumer level, primarily due to uncertainty in identifying the freshness and safety of food items. Traditional approaches to assessing food quality, such as visual inspection, reliance on expiry dates, or personal judgment, often lack consistency and accuracy. Recent developments in artificial intelligence and computer vision have opened new possibilities for automated food freshness assessment. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable effectiveness in image-based classification across domains including healthcare, agriculture, and object recognition. When applied to food analysis, these models can objectively evaluate visual attributes such as color variations, texture changes, and surface characteristics. Furthermore, incorporating intelligent recommendation mechanisms enhances system usability by transforming classification results into practical guidance. This work introduces an AI-driven approach that combines image-based food freshness detection with recipe recommendations,

enabling users to make informed consumption decisions. The proposed system supports sustainable food practices by encouraging timely food utilization and minimizing avoidable waste.

2. Literature Review

Recent studies highlight the growing application of artificial intelligence and computer vision techniques in food quality assessment. Traditional food freshness evaluation methods rely on human inspection, chemical analysis, or expiry labels, which are often subjective, time-consuming, and inconsistent. These limitations have motivated researchers to explore automated and image-based solutions for food quality monitoring. Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance in image classification tasks. LeCun et al. (2015) emphasized the ability of CNNs to automatically learn hierarchical visual features, making them suitable for complex image-based analysis. Krizhevsky et al. (2012) further established the effectiveness of CNNs through large-scale image recognition tasks, laying the foundation for their adoption in various domains. Several studies have applied CNNs to agricultural and food-related

problems. Mohanty et al. (2016) successfully employed deep learning models for plant disease detection using leaf images, achieving high classification accuracy. Kamilaris and Prenafeta-Boldú (2018) reviewed the application of deep learning in agriculture and reported significant improvements in visual inspection tasks, including crop monitoring and food quality evaluation. Similarly, Singh and Jain (2021) discussed the potential of computer vision techniques in assessing food freshness based on visual attributes such as color and texture. While existing research primarily focuses on classification and detection, limited attention has been given to post-classification decision support. Most systems stop at identifying food quality without offering actionable guidance to users. Addressing this gap, the proposed work integrates food freshness detection with a recipe recommendation mechanism. By combining CNN-based image analysis with intelligent recommendation, the system not only identifies freshness levels but also supports efficient food utilization, contributing to waste reduction and sustainable consumption practices.

3. System Design

3.1. System Architecture

The proposed system architecture is designed to perform automated food freshness detection and recipe recommendation in a modular and scalable manner. The system accepts a food image as input from the user and processes it through multiple stages to generate meaningful outputs. Initially, the input image undergoes preprocessing to ensure uniformity and compatibility with the classification model. The preprocessed image is then passed to a Convolutional Neural Network (CNN) that analyzes visual characteristics such as color distribution, texture variations, and surface patterns to determine the freshness level of the food item. Based on the predicted freshness category - fresh, medium, or spoiled, the output is forwarded to a recipe recommendation module. This module selects suitable recipes by interacting with an external recipe API or a predefined recipe database. The final output presented to the user includes the freshness classification along with appropriate recipe

suggestions, enabling informed food usage decisions. The modular design allows each component to operate independently, ensuring ease of maintenance and future enhancements.

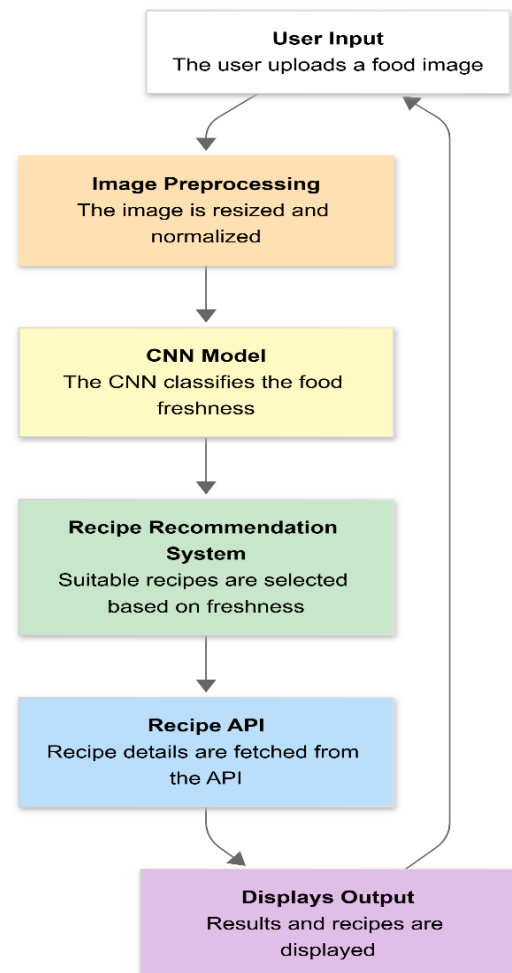


Figure 1 Architecture of The Proposed System

3.2. Techniques Used

The system employs image-based analysis techniques to assess food freshness. Image preprocessing through normalization is applied to scale pixel values and stabilize model training. A CNN-based deep learning approach is used for feature extraction and classification, enabling the model to learn complex visual patterns associated with food spoilage. A rule-based recommendation strategy is adopted to map freshness categories to suitable recipe suggestions, enhancing system usability.

Table 1 Tools used in the Proposed System

Tool	Purpose
Python	Core programming language
TensorFlow & Keras	CNN model development
Google Colab	Model training and testing
Kaggle Dataset	Image data source
Recipe API	Recipe recommendation

4. Methodology

The development of the proposed food freshness detection and recipe recommendation system was carried out using a systematic research approach to achieve dependable performance and practical applicability. The overall methodology consists of five key stages: problem identification, dataset processing, model construction, system integration, and performance evaluation.

4.1.Problem Identification

The first stage focused on examining the difficulties faced by consumers in assessing food freshness in household and small-scale environments. Common practices such as relying on visual inspection or expiry labels often fail to accurately represent actual food quality. As a result, usable food is frequently discarded prematurely, while in some cases spoiled food may be consumed, posing health concerns. These challenges underscored the necessity for an automated solution capable of objectively evaluating food freshness from images and offering meaningful guidance to users.

4.2.Dataset Processing

A publicly available image dataset was sourced from Kaggle, consisting of banana images captured at various ripeness stages. The dataset included samples corresponding to fresh, intermediate, and spoiled conditions. To maintain uniformity and improve learning efficiency, all images were resized to a predefined resolution and normalized to scale pixel values consistently. Data augmentation operations such as image rotation, horizontal flipping, and zooming were applied to enhance dataset variability

and mitigate overfitting. The processed dataset was subsequently partitioned into training, validation, and testing sets.

4.3.CNN Model Construction

A Convolutional Neural Network (CNN) was employed due to its strong capability in handling image-based classification problems. The model architecture was designed to learn discriminative visual features, including changes in color, texture, and surface patterns related to food freshness. Training was performed using the prepared dataset, while validation data supported hyperparameter tuning, including batch size, learning rate, and network depth. Regularization strategies were applied to improve generalization and reduce overfitting.

4.4.System Integration

After achieving stable classification performance, the trained CNN model was incorporated into the overall system framework. The system allows users to upload food images, which are then preprocessed and passed through the trained model for freshness prediction. Based on the predicted class—fresh, medium, or spoiled—the recipe recommendation component is activated. This module communicates with an external recipe API to fetch relevant recipes and preparation instructions, encouraging efficient use of food items that remain suitable for consumption.

4.5.Performance Evaluation

The integrated system was assessed using previously unseen test images to evaluate its predictive accuracy and reliability. Key performance indicators, including classification accuracy and loss, were examined to validate the model's effectiveness. Additionally, end-to-end system testing ensured smooth interaction between the freshness detection and recipe recommendation modules, confirming that appropriate outputs were generated for each freshness category.

5. Results and Discussion

The proposed system was evaluated using a diverse set of food images representing different freshness levels. The performance of the CNN model and the effectiveness of the recipe recommendation workflow were analyzed based on accuracy,

consistency, and practical usability.

5.1. Model Performance

The CNN model demonstrated strong capability in distinguishing between fresh, medium, and spoiled food images. During testing, the model achieved an accuracy in the range of 88–92%, indicating reliable classification performance. The model effectively captured visual indicators such as color darkening, texture degradation, and surface defects associated with food spoilage. Minor misclassifications were observed in cases where lighting conditions or background variations affected image clarity.

5.2. Generalization and Robustness

The model performed consistently across images with different lighting conditions and orientations, largely due to the application of data augmentation during training. Images taken under varied illumination and background settings were classified accurately in most cases, demonstrating the robustness of the trained model. These results indicate that the system can be used in real-world household environments without strict image capture constraints.

5.3. Recipe Recommendation Output

The recipe recommendation module successfully mapped freshness categories to suitable recipe suggestions. For fresh food items, the system provided a wide variety of recipes, while medium quality items triggered recommendations for quick-to-prepare dishes. When food was classified as spoiled, the system appropriately refrained from suggesting recipes, emphasizing food safety. The inclusion of ingredients and step-by-step instructions enhanced user usefulness and decision making.

5.4. Discussion

The experimental outcomes indicate that the CNN-based approach effectively captures visual cues such as color and texture variations associated with food freshness, resulting in reliable classification performance. The stable behavior observed between training and validation results suggests that normalization contributed to improved learning and generalization. Minor misclassifications are mainly attributed to visual similarities between freshness stages and variations in image lighting conditions, highlighting the limitations of purely vision-based

analysis. Integrating recipe recommendations adds practical value by converting freshness predictions into actionable guidance for users, supporting informed food utilization and waste reduction.

Conclusion

This paper presented an AI-based food freshness detection and recipe recommendation system using CNN-based image classification. The system effectively categorizes food items based on visual appearance and provides actionable recipe suggestions to reduce food waste. The software-based approach ensures low cost and ease of deployment, making it suitable for household and small-scale applications. Future work includes extending the system to multiple food categories and improving robustness under diverse environmental conditions.

Acknowledgement

The authors would like to express their sincere gratitude to the faculty mentors and the institution for their guidance and support throughout the course of this project. This work was carried out using standard institutional computing facilities and open-source software tools. No external financial support or funding was received for the completion of this work.

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